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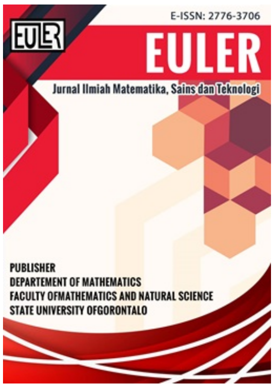

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Research Article

Comparative Analysis of Grey GM(1,1) and Grey Verhulst Models for Forecasting Electricity Consumption in Indonesia

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ABSTRACT. *Electricity energy demand in Indonesia continues to increase in line with economic development, technological advancement, and population growth. This condition necessitates appropriate energy planning to ensure a stable electricity supply. Electricity consumption forecasting is required to predict future demand and to serve as a basis for formulating sustainable energy policies. However, studies comparing different grey forecasting models for Indonesia's electricity consumption remain limited, particularly in identifying the most suitable model for its growth characteristics. This study aims to compare the performance of two models within Grey System Theory, namely the Grey Model GM(1,1) and the Grey Verhulst model, in forecasting electricity consumption in Indonesia. The data used consist of annual electricity consumption data for the period 2000–2024, obtained from the official websites of Statistics Indonesia (BPS) and the Ministry of Energy and Mineral Resources (ESDM). The analysis stages include model construction, parameter estimation, forecasting, and accuracy evaluation using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results indicate that the Grey Verhulst model outperforms the GM(1,1) model, with an RMSE of 10,955.97, an MAE of 9,233.64, and a MAPE of 5%, whereas the GM(1,1) model yields an RMSE of 23,562.39, an MAE of 15,151.57, and a MAPE of 9%. These results suggest that the Grey Verhulst model provides a better fit for the observed data, which exhibits nonlinear growth behavior with a tendency toward saturation. The best-performing model, namely the Grey Verhulst model, produces a forecast of electricity consumption for the year 2025 of 388,025 GWh. This result is expected to serve as a reference for national electricity policy planning.*

1. Introduction

Technological advancement and increased social mobility have driven the rising demand for electricity across various sectors, including residential, industrial, commercial, and public sectors. Electricity has become a fundamental necessity supporting economic activities and improving quality of life; therefore, its availability, quality, and sustainability must be managed optimally [1, 2]. Along with the government's increasing focus on regional development and the expansion of energy access, national electricity demand is projected to continue rising in the long term. In this context, accurate and reliable forecasting models are essential not only to predict future demand but also to support data-driven decision-making in energy planning under conditions of uncertainty.

According to the Indonesia Energy Outlook 2023 published by the National Energy Council, national electricity demand is projected to increase significantly from 313 TWh in 2022 to 479–488 TWh by 2033, with the highest growth expected in the transportation sector as a result of policies promoting electric vehicles [3]. This upward trend is also reflected in Indonesia's per capita electricity consumption, which has increased steadily since 2017, reaching 1,285 kWh in 2023, and is targeted to reach 1,408 kWh in 2024 [4]. These conditions

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highlight the importance of accurate electricity consumption forecasting as a foundation for national electricity planning and policy formulation.

Electricity consumption forecasting is commonly conducted using time series analysis, which utilizes historical data to predict future demand [5]. However, classical time series methods generally require a relatively large amount of historical data to achieve optimal forecasting performance [6]. Under conditions of limited data availability, the Grey Model GM(1,1) serves as an alternative, as it is capable of producing forecasts with minimal data and without strict assumptions regarding data patterns [7, 8]. GM(1,1) is effective for data exhibiting linear or monotonically exponential growth patterns and is particularly suitable for short-term forecasting [9].

Nevertheless, GM(1,1) has limitations in handling data with high fluctuations or nonlinear growth patterns, leading to a decline in accuracy for long-term forecasting [10]. To address these limitations, several extended models have been developed, one of which is the Grey Verhulst model, designed to capture S-shaped growth patterns with an upper bound [11]. The Grey Verhulst model is considered more adaptive and accurate for data characterized by limited growth and high variability [9]. Despite these theoretical differences, previous studies generally evaluate these models separately or in different application contexts, resulting in a lack of direct empirical comparison under the same dataset and conditions. In the context of Indonesia's electricity consumption, empirical evidence comparing the performance of GM(1,1) and the Grey Verhulst model remains very limited, particularly in assessing their suitability for national-level forecasting. This limitation highlights a research gap in identifying which grey model is more appropriate for capturing the underlying characteristics of Indonesia's electricity consumption data.

Addressing this gap is important not only from a methodological perspective but also for improving the reliability of energy demand forecasting to support national policy decisions. This study contributes to the literature by providing a direct and systematic comparison of two widely used grey forecasting models using the same dataset and evaluation framework. Based on this background, this study aims to compare the performance of the Grey Model GM(1,1) and the Grey Verhulst model in forecasting electricity consumption in Indonesia.

2. Methods

Data used in this study are secondary data obtained from the official websites of Statistics Indonesia [12] and the Directorate General of Electricity of the Ministry of Energy and Mineral Resources [13]. The dataset consists of annual electricity consumption data covering the period 2000–2024.

In the initial stage, descriptive analysis is conducted on Indonesia's electricity consumption data for the period 2000–2024, followed by forecasting using the Grey Model GM(1,1), which involves constructing the original data sequence, forming the Accumulated Generating Operation (AGO) and Mean Generating Operation (MGO) sequences, estimating model parameters, and computing predicted values. In parallel, forecasting is also performed using the Grey Verhulst model through the construction of the original data sequence, the Inverse Accumulated Generating Operation (IAGO), the Accumulated Generating Operation (AGO), and the Mean Generating Operation (MGO) sequences, followed by parameter estimation and prediction. Subsequently, the forecasting results from the GM(1,1) and Grey Verhulst models are compared based on model performance evaluation, and the overall research procedure is illustrated in a flowchart presented in Figure 1.

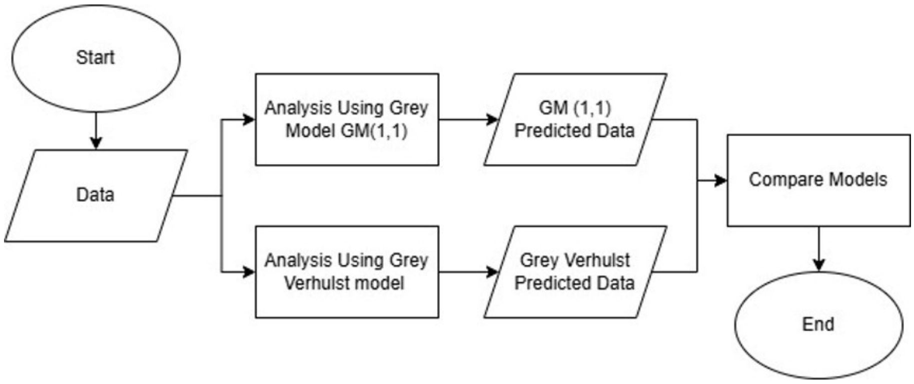

Figure 1. Research Flowchart

2.1. GM(1,1) Model

In Grey System Theory, originally introduced by Julong [14], a dynamic model based on differential equations, known as the Grey differential model or Grey Model (GM), is developed. One of the most widely used models in the field of economics is GM(1,1), in which the differential process is performed once and involves only a single variable. In addition to generating sequences, the main components in the development of Grey models include Grey derivatives, parallel shooting, and Grey differential equations.

In general, forecasting using the GM(1,1) model involves three main operations, namely the Accumulated Generating Operation (AGO), the Inverse Accumulated Generating Operation (IAGO), and the Grey Model itself. At this stage, the Mean Generating Operation (MGO) is also introduced.

The analytical steps of the GM(1,1) model can be described as follows [15, 16]:

1. Constructing the original data sequence, denoted by $X^{(0)}$

$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n)\right\}. \tag{1}$$

2. Generating a new data sequence using AGO
   The AGO sequence, denoted by $X^{(1)}$, is obtained by accumulating the original data sequence $X^{(0)}$:

$$\begin{aligned} X^{(1)} &= \left\{x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \ldots, x^{(1)}(n)\right\}, \\ x^{(1)}(k) &= \sum_{t=1}^{k} x^{(0)}(t), \quad k = 1, 2, 3, \ldots, n. \end{aligned} \tag{2}$$

3. Forming the MGO sequence
   The MGO sequence, denoted by $Z^{(1)}$, represents the mean or background value between $x^{(1)}(k)$ and $x^{(1)}(k-1)$. This sequence is used to estimate the model parameters a and b:

$$\begin{aligned} Z^{(1)} &= \left\{z^{(1)}(1), z^{(1)}(2), \ldots, z^{(1)}(n)\right\}, \\ z^{(1)}(k+1) &= 0.5\left(x^{(1)}(k) + x^{(1)}(k-1)\right). \end{aligned} \tag{3}$$

4. Constructing matrices $\mathbf{B}$ and $\mathbf{y}_N$

$$\mathbf{B} = \begin{bmatrix} -0.5\left(x^{(1)}(2) + x^{(1)}(1)\right) & 1 \\ \vdots & \vdots \\ -0.5\left(x^{(1)}(k) + x^{(1)}(k-1)\right) & 1 \end{bmatrix}, \quad \mathbf{y}_N = \begin{bmatrix} x^{(0)}(2) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}. \tag{4}$$

5. Estimating parameters a and b using the Least Squares method
The original and generated data sequences in eq. (1) and (2) are used to construct a first-order linear differential equation:

$$\frac{dx^{(1)}(k)}{dt} + ax^{(1)}(k) = b, \tag{5}$$

where $x^{(1)}(t)$ is the AGO-generated data, and a and b are the parameters to be estimated. Based on the definition of a derivative, the first derivative is expressed as:

$$\frac{dx^{(1)}(k)}{dt} = \lim_{\Delta t \to 0} \frac{x^{(1)}(k+\Delta t) - x^{(1)}(k)}{\Delta t}. \tag{6}$$

Since the data are discrete, the derivative is approximated by the difference between two consecutive observations by choosing the smallest time interval $\Delta t = 1$:

$$\frac{dx^{(1)}(k)}{dt} \approx x^{(1)}(k+1) - x^{(1)}(k).$$

To represent $x^{(1)}(k)$ over the interval from k to $k+1$, the background value defined in eq. (3) is used. Thus, the GM(1,1) model in eq. (5) can be rewritten as:

$$x^{(1)}(k+1) - x^{(1)}(k) + az^{(1)}(k+1) = b. \tag{7}$$

Based on the AGO definition:

$$x^{(1)}(1) = x^{(0)}(1), \quad x^{(1)}(2) = x^{(0)}(1) + x^{(0)}(2),$$

which implies:

$$x^{(0)}(2) = x^{(1)}(2) - x^{(1)}(1)$$

Therefore, the equation $x^{(1)}(2) - x^{(1)}(1) + az^{(1)}(2) = b$ is equivalent to $x^{(0)}(2) + az^{(1)}(2) = b$. Hence, eq. (5) can be expressed as:

$$x^{(0)}(k) + az^{(1)}(k) = b, \quad k = 2, 3, \ldots, n. \tag{8}$$

Using the least squares method, the parameter estimates a and b are obtained as:

$$\hat{\mathbf{a}} = \begin{bmatrix} a \\ b \end{bmatrix} = (\mathbf{B}^T\mathbf{B})^{-1}\mathbf{B}^T\mathbf{y}_N. \tag{9}$$

6. Computing the predicted values
The solution of eq. (5) based on the estimated parameters a and b is given by:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a}. \tag{10}$$

To obtain the predicted values of the original data at time $k+1$, the IAGO is applied:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k). \tag{11}$$

2.2. Grey Verhulst Model

The Grey Verhulst model was first introduced by Pierre François Verhulst, a German biologist, in 1845 [17]. Verhulst explained that the growth of a system does not always increase continuously. In contrast to exponential growth theory, this model demonstrates that the growth rate gradually slows over time due to limiting factors, eventually reaching a saturation point. This process forms an S-shaped logistic curve, which represents an initial slow growth phase, followed by rapid growth, and finally a deceleration until growth ceases [15].

The analytical procedures of the Grey Verhulst model can be described as follows [15, 16, 18, 19]:

1. Constructing the original data sequence
$$X^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)\right\}. \tag{12}$$
2. Performing the Inverse Accumulated Generating Operation (IAGO)
The IAGO is applied to $X^{(0)}$ to obtain $\tilde{X}^{(0)}$ using the following equations:
$$\begin{aligned} \tilde{X}^{(0)} &= \left\{\tilde{x}^{(0)}(1), \tilde{x}^{(0)}(2), \dots, \tilde{x}^{(0)}(n)\right\}, \\ \tilde{x}^{(0)}(k) &= x^{(0)}(k) - x^{(0)}(k-1), \quad k \geq 2, \\ \tilde{x}^{(0)}(1) &= x^{(0)}(1). \end{aligned} \tag{13}$$
3. Generating a new data sequence using AGO
The Accumulated Generating Operation (AGO) produces a new sequence denoted by $\tilde{X}^{(1)}$, which is obtained by accumulating the elements of $\tilde{X}^{(0)}$:
$$\tilde{X}^{(1)} = \left\{\tilde{x}^{(1)}(1), \tilde{x}^{(1)}(2), \tilde{x}^{(1)}(3), \dots, \tilde{x}^{(1)}(n)\right\}, \tag{14}$$
where
$$\tilde{x}^{(1)}(k) = \sum_{t=1}^{k} \tilde{x}^{(0)}(t), \quad k = 1, 2, 3, \dots, n.$$
4. Forming the Mean Generating Operation (MGO) sequence
The MGO sequence, denoted by $Z^{(1)}$, represents the mean or background value between $\tilde{x}^{(1)}(k)$ and $\tilde{x}^{(1)}(k-1)$. This sequence is used to estimate the parameters a and b:
$$Z^{(1)} = \left\{z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)\right\}, \tag{15}$$
where
$$z^{(1)}(k) = 0.5\left(\tilde{x}^{(1)}(k) + \tilde{x}^{(1)}(k-1)\right).$$
5. Constructing matrices $\mathbf{B}$ and $\mathbf{y}_N$
$$\begin{aligned} \mathbf{B} &= \begin{bmatrix} -0.5\left(\tilde{x}^{(1)}(2) + \tilde{x}^{(1)}(1)\right) & \left(0.5\left(\tilde{x}^{(1)}(2) + \tilde{x}^{(1)}(1)\right)\right)^2 \\ -0.5\left(\tilde{x}^{(1)}(3) + \tilde{x}^{(1)}(2)\right) & \left(0.5\left(\tilde{x}^{(1)}(3) + \tilde{x}^{(1)}(2)\right)\right)^2 \\ \vdots & \vdots \\ -0.5\left(\tilde{x}^{(1)}(k) + \tilde{x}^{(1)}(k-1)\right) & \left(0.5\left(\tilde{x}^{(1)}(k) + \tilde{x}^{(1)}(k-1)\right)\right)^2 \end{bmatrix}, \\ \mathbf{y}_N &= \begin{bmatrix} \tilde{x}^{(0)}(2) \\ \vdots \\ \tilde{x}^{(0)}(n) \end{bmatrix}. \end{aligned} \tag{16}$$
6. Estimating parameters a and b using the Least Squares method
The Grey Verhulst model is established by constructing a first-order differential equation for $\tilde{X}^{(1)}$:
$$\tilde{x}^{(1)}(k) + az^{(1)}(k) = b\left(z^{(1)}(k)\right)^2, \tag{17}$$

which leads to the following continuous form:

$$\frac{d\tilde{x}^{(1)}(t)}{dt} + a\tilde{x}^{(1)}(t) = b\left(\tilde{x}^{(1)}(t)\right)^2. \tag{18}$$

Using the least squares method, the parameter estimates a and b are obtained as:

$$\hat{\mathbf{a}} = \begin{bmatrix} a \\ b \end{bmatrix} = (\mathbf{B}^T\mathbf{B})^{-1}\mathbf{B}^T\mathbf{y}_N. \tag{19}$$

7. Computing the predicted values
   The solution of eq. (18) based on the estimated parameters a and b is given by:

$$\hat{\tilde{x}}^{(1)}(k+1) = \frac{a\tilde{x}^{(1)}(1)}{b\tilde{x}^{(1)}(1) + \left(a - b\tilde{x}^{(1)}(1)\right)e^{ak}}. \tag{20}$$

2.3. *Forecasting Accuracy*

To evaluate the predictive performance of the Grey forecasting models employed in this study, namely the GM(1,1) and Grey Verhulst models, forecasting accuracy tests are conducted. These tests are used to assess how closely the predicted values generated by each Grey model approximate the actual observed data. When a forecasting method is deemed suitable for modeling the underlying data pattern, the selection of the most appropriate model is determined based on the magnitude of the forecasting errors produced [20].

It is widely recognized that no forecasting model, including Grey Models, is capable of predicting future conditions with perfect accuracy, particularly when dealing with limited, uncertain, or incomplete data. Consequently, each model inevitably generates prediction errors. A smaller error value indicates that the forecasting results are closer to the actual conditions and that the model exhibits better predictive performance.

In this study, the accuracy of the GM(1,1) and Grey Verhulst models is evaluated using several commonly applied error measures, including the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

In this study, the selection of RMSE, MAE, and MAPE is intended to provide a comprehensive evaluation of model performance from different perspectives. RMSE is sensitive to large errors and is useful for penalizing significant deviations, while MAE provides a more robust measure of average error magnitude without emphasizing extreme values. MAPE, on the other hand, expresses forecasting accuracy in percentage terms, allowing for easier interpretation and comparison across different scales.

However, it is acknowledged that MAPE has certain limitations, particularly when the actual values are close to zero, which may lead to inflated or undefined error values. In this study, the electricity consumption data are strictly positive and relatively large in magnitude, thereby minimizing the potential bias associated with MAPE. Therefore, the combined use of these three metrics is considered sufficient to provide a balanced and reliable evaluation of forecasting performance.

2.3.1. Root Mean Square Error (RMSE)

RMSE is a statistical indicator used to measure the overall accuracy of forecasting models by quantifying the square root of the average squared differences between the actual observations and the predicted values. RMSE places greater emphasis on large errors, making it particularly useful for assessing the stability of Grey model predictions:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \hat{x}_t)^2}. \tag{21}$$

2.3.2. Mean Absolute Error (MAE)

MAE measures the average magnitude of the absolute differences between actual values and predicted values without considering the direction of the errors. In the context of Grey Models, a smaller MAE value indicates that the GM(1,1) or Grey Verhulst model provides predictions that are, on average, closer to the observed electricity consumption data:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|x_t - \hat{x}_t\right|. \tag{22}$$

2.3.3. Mean Absolute Percentage Error (MAPE)

MAPE evaluates forecasting accuracy by expressing the absolute prediction errors as percentages of the actual values. This measure facilitates a relative comparison of forecasting performance between the GM(1,1) and Grey Verhulst models, particularly when the scale of the data varies over time:

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{x_t - \hat{x}_t}{x_t}\right|. \tag{23}$$

where n denotes the number of observations, x_t represents the actual value at time t, and $\hat{x}_t$ represents the forecasted value at time t.

3. Results and Discussion

An overview of electricity consumption data in Indonesia from 2000 to 2024 is presented in Figure 2. The data used are annual data measured in GWh (Gigawatt-hours) obtained from official sources, namely the Central Bureau of Statistics (BPS) and the Ministry of Energy and Mineral Resources (ESDM).

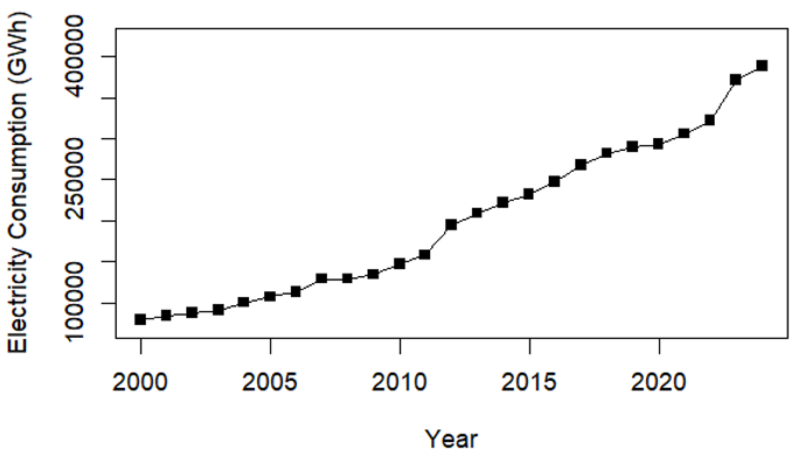

Figure 2. Trend of Electricity Consumption (GWh) in Indonesia

Based on Figure 2, electricity consumption in Indonesia shows a consistently increasing trend over time. In 2000, electricity consumption was recorded at 79,164.81 GWh and gradually increased to 388,025 GWh in 2024. Over this 24-year period, total electricity consumption increased by more than fourfold. This increase reflects the growing demand for electricity in line with economic development, industrialization processes, and population growth in Indonesia.

However, the growth rate of electricity consumption does not remain constant each year. In general, the annual increase in electricity consumption is within a range of less than 10%. Nevertheless, certain periods exhibit higher growth rates, exceeding 10% and approaching 20%. One notable example occurred during the 2011–2012 period, when electricity consumption increased by 22.97%. After this sharp increase, the growth rate declined again to below 10% in the following year.

This growth pattern indicates phases of relatively slow growth, followed by a period of rapid increase, and then a slowdown before rising again in subsequent periods. Such variations in growth rates suggest that the electricity consumption data tend to follow an S-shaped growth pattern (S-curve). This indication is further supported by the observed transition from an initial slow growth phase to a period of rapid increase, followed by a gradual slowdown, which is consistent with the general characteristics of logistic growth behavior.

3.1. Forecasting Results Using GM(1,1) Model

The GM(1,1) model was first applied to forecast electricity consumption in Indonesia. Based on parameter estimation calculated using eq. (9), the GM(1,1) model parameters were obtained as: $a = -0.07$, $b = 80{,}406.38$. Using these parameters, the GM(1,1) forecasting model was constructed to generate predicted values of electricity consumption, which were computed using eq. (11). The comparison between the actual data and the GM(1,1) predicted values is presented in Table 1, while the graphical comparison is illustrated in Figure 3.

Table 1. Actual Data and GM(1,1) Predicted Data

Year	Actual Data	GM(1,1) Predicted Data	Year	Actual Data	GM(1,1) Predicted Data
2000	79164.81	79164.81	2013	208935.00	181176.02
2001	84520.38	82838.58	2014	221296.00	193385.13
2002	87088.74	88420.91	2015	232447.11	206416.97
2003	90440.94	94379.42	2016	247416.06	220327.01
2004	100097.46	100739.47	2017	267453.99	235174.42
2005	107032.23	107528.11	2018	282031.11	251022.37
2006	112609.80	114774.22	2019	289340.82	267938.28
2007	129018.81	122508.63	2020	293465.27	285994.12
2008	129018.81	130764.25	2021	305627.28	305266.71
2009	134207.46	139576.20	2022	322336.67	325838.04
2010	147297.46	148981.97	2023	370997.44	347795.64
2011	157992.66	159021.57	2024	388025.00	371232.91
2012	194289.00	169737.73	2025		396249.58

The results show that the predicted values generally follow the increasing trend of the observed data. Minor deviations occur during the early observation period, but the predicted values gradually approach the actual values toward the end of the time series. A closer examination shows that the GM(1,1) model tends to underestimate electricity consumption during periods of rapid growth, particularly around 2011–2013, where the deviation between actual and predicted values becomes more pronounced. In contrast, the model performs relatively better during periods of stable growth toward the end of the observation period.

Based on the GM(1,1) model, electricity consumption in Indonesia is projected to reach 396,249.58 GWh in 2025, indicating an increase of approximately 8,224.58 GWh compared

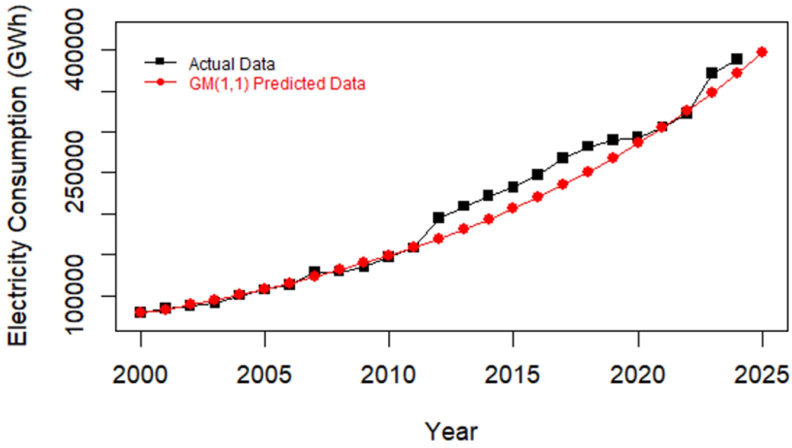

Figure 3. GM(1,1) Forecast of Electricity Consumption

with the consumption level recorded in 2024.

To evaluate the forecasting performance of the model, three error metrics were used: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), calculated using eq. (21) to eq. (23). The results show that the GM(1,1) model produces an RMSE of 23,562.39, MAE of 15,151.57, and MAPE of 9%. The MAPE value below 10% indicates that the GM(1,1) model provides an acceptable level of forecasting accuracy.

3.2. Forecasting Results Using Grey Verhulst Model

In addition to the GM(1,1) model, forecasting was also performed using the Grey Verhulst model. This model is particularly suitable for data that exhibit logistic growth patterns characterized by an S-shaped curve. The parameter estimation results for the Grey Verhulst model, calculated using eq. (19), are given as: $a = -0.07$, $b = -3.57 \times 10^{-8}$. Using these parameters, the Grey Verhulst model was used to generate the predicted values of electricity consumption, which were computed using eq. (20). The comparison between the predicted and actual data is presented in Table 2 and Figure 4.

Table 2. Actual Data and Grey Verhulst Predicted Data

Year	Actual Data	Grey Verhulst Predicted Data	Year	Actual Data	Grey Verhulst Predicted Data
2000	79164.81	79164.81	2013	208935.00	193483.60
2001	84520.38	84939.05	2014	221296.00	206723.28
2002	87088.74	91115.03	2015	232447.11	220761.41
2003	90440.94	97717.78	2016	247416.06	235631.24
2004	100097.46	104773.47	2017	267453.99	251365.31
2005	107032.23	112309.36	2018	282031.11	267995.14
2006	112609.80	120353.80	2019	289340.82	285550.88
2007	129018.81	128936.18	2020	293465.27	304060.85
2008	129018.81	138086.86	2021	305627.28	323551.13
2009	134207.46	147837.09	2022	322336.67	344045.09
2010	147297.46	158218.92	2023	370997.44	365562.90
2011	157992.66	169265.07	2024	388025.00	388121.01
2012	194289.00	181008.77	2025		411731.66

The results indicate that the Grey Verhulst model closely follows the overall trend of electricity consumption during the observation period. The Grey Verhulst model demonstrates improved performance during periods of accelerated growth, as it is able to adjust more effectively to changes in growth rates. However, slight deviations are still observed in the early years, indicating that the model requires sufficient data structure to capture nonlinear patterns accurately. Such variations in growth rates suggest that the electricity consumption data tend to follow an S-shaped growth pattern.

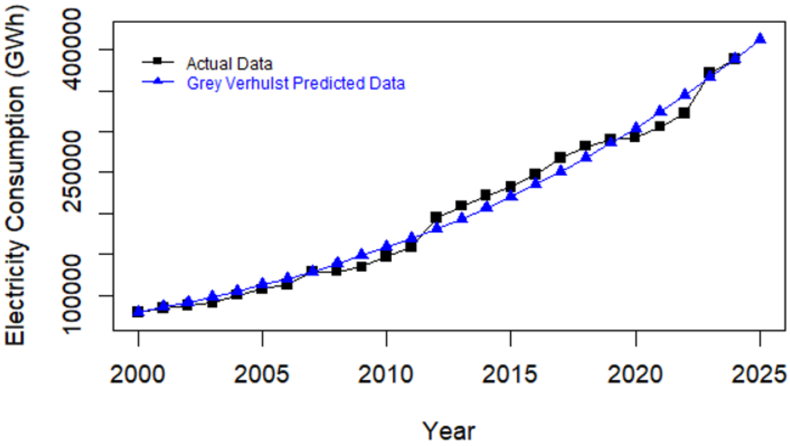

Figure 4. Grey Verhulst Forecast of Electricity Consumption

Based on the model estimation, electricity consumption in Indonesia is predicted to reach 411,731.66 GWh in 2025, representing an increase of approximately 23,706.66 GWh compared with the 2024 consumption level. The accuracy evaluation results, calculated using eq. (21) to eq. (23), show that the Grey Verhulst model produces an RMSE of 10,955.97, MAE of 9,233.64, and MAPE of 5%. These values indicate a high level of forecasting accuracy, particularly as the MAPE value is substantially below the 10% threshold commonly used to indicate strong predictive performance.

3.3. Model Comparison

To determine the most appropriate model for forecasting electricity consumption in Indonesia, the predictive performances of the GM(1,1) and Grey Verhulst models were compared using RMSE, MAE, and MAPE calculated using eq. (21) to eq. (23). The comparison results are summarized in Table 3.

Table 3. Comparison of the Accuracy of GM(1,1) and Grey Verhulst Models

Method	RMSE	MAE	MAPE
GM(1,1)	23562.39	15151.57	9%
Grey Verhulst	10955.97	9233.64	5%

The results show that the Grey Verhulst model consistently produces lower error values than the GM(1,1) model across all evaluation metrics. Specifically, the Grey Verhulst model achieves an RMSE of 10,955.97, MAE of 9,233.64, and MAPE of 5%, while the GM(1,1) model yields higher errors with RMSE 23,562.39, MAE 15,151.57, and MAPE 9%.

These findings indicate that the Grey Verhulst model provides better forecasting performance for the electricity consumption data in Indonesia. This result is consistent with the earlier observation that the data exhibit characteristics of an S-shaped growth pattern. Since the Grey Verhulst model is specifically designed to capture logistic growth dynamics, it is better able to represent the underlying structure of the data compared with the GM(1,1) model.

Therefore, the Grey Verhulst model is considered more suitable for forecasting electricity consumption in Indonesia.

From a practical perspective, the difference in forecasting accuracy between the two models is meaningful, as lower error values can lead to more reliable estimates of future electricity demand. This is particularly important for energy planning, where overestimation or underestimation may result in inefficient resource allocation or supply shortages.

4. Conclusion

This study compared the performance of the GM(1,1) and Grey Verhulst models in forecasting electricity consumption in Indonesia using annual data from 2000 to 2024. The results show that electricity consumption in Indonesia exhibits a consistently increasing trend throughout the observation period. However, the rate of growth varies over time, with an initial phase of relatively slow growth followed by a period of faster increase and subsequently a gradual slowdown. Such dynamics indicate that the growth pattern of electricity consumption resembles an S-shaped curve (S-curve).

Based on the forecasting accuracy evaluation, the Grey Verhulst model demonstrates better performance than the GM(1,1) model. The Grey Verhulst model produces a Mean Absolute Percentage Error (MAPE) of 5%, which is lower than the 9% obtained by the GM(1,1) model. Similarly, the Grey Verhulst model also yields smaller values of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), with RMSE of 10,955.97 and MAE of 9,233.64, compared to the GM(1,1) model which produces RMSE of 23,562.39 and MAE of 15,151.57. These results indicate that the Grey Verhulst model provides more accurate forecasting performance for the electricity consumption data.

Furthermore, the forecasting results obtained using the Grey Verhulst model show predicted values that closely follow the actual electricity consumption trend, indicating a high level of predictive accuracy. This finding suggests that the Grey Verhulst model is more capable of capturing the growth characteristics of electricity consumption in Indonesia, particularly when the data exhibit an S-shaped growth pattern. This study contributes to the literature by providing a comparative evaluation of GM(1,1) and Grey Verhulst models using a consistent dataset in the Indonesian context. However, the comparison is primarily based on in-sample performance, and thus the results should be interpreted with caution. Future studies may consider incorporating out-of-sample validation to further improve forecasting reliability.

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